# Mining electronic negotiation messages – an exploratory evaluation and first steps

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## Abstract

Analysing negotiation communication in an electronic setting is a challenging task. During recent years, many researchers have tried to explain the differences between successful and failed negotiation applying a great variety of approaches, ranging from linguistic analyses over phase identification to psychological analyses of the discourse during a negotiation. The aim of this paper is to provide the foundation to analyse negotiation communication with a machine learning approach. To this end, a review of existing and related research is given, the applicability of machine learning techniques on electronic negotiations is discussed and, in a first step of the process, different methods of feature selection are reviewed to find the most applicable technique in the setting given.

## 1 Introduction

Among the various fields of electronic negotiation research, the analysis of communication between the negotiators is one of the most important and also multifaceted ones. In electronic negotiations, the medium used to communicate imposes several natural restrictions on the negotiators, e.g. they are not able to see or hear each other, there are no non-verbal cues as the negotiators are restricted to textual communication only. It is often argued that this leads to an oversimplification of the negotiation process – which is most of the time considered as one of the major drawbacks of electronic negotiation [23].

However, from a researchers' point of view this restriction has an interesting effect: The whole communication between the negotiators can now be easily recorded, without having to pay attention to gestures or mimics etc. which are more difficult to document. Especially in textual negotiations via an electronic negotiation support system (NSS) – which is the kind of negotiation process this proposal focuses on – it is quite easy to monitor the communication process between the negotiators. Apart from the fact that the negotiators' perception of negotiation messages can't be recorded that easily, there are still traces of the reaction in the reply of a negotiator to a message. This can provide researchers with valuable insights into what constitutes "good" negotiation communication and how to detect arising conflicts at an early stage of the negotiation – for example with the intention to intervene at a certain point to prevent negotiations from escalating, and thus providing proactive support, e.g. as a component of an NSS.

Furthermore, there exist further advantages of asynchronous electronic negotiation. Friedman and Currall [12] outline several advantages of E-Mail-Communication versus face-to-face discussions – these differences are taken up and applied to electronic negotiation communication by Pesendorfer and Köszegi. [21]: According to Friedman and Currall, the two main advantages are *reviseability* and *reviewability*. While reviewability describes the possibility to read a communication partners' statement as often as required (and thus decreasing the likelihood of misunderstandings), reviseability is the opportunity to revise one's own statements and messages before sending (and thus generating well-considered messages).

In a more general way, this discussion is also reflected in the main theoretical perspectives on online interpersonal communication, especially regarding the joint fulfilment of a task. From the perspective of the *cues-filtered-out* model [5], the impersonality of a computer-mediated interaction would make a consensus in a joint decision making situation less likely. Media Richness Theory [6] follows a similar path of argumentation, by judging textual messages as a rather inefficient medium for a complex task such as electronic negotiations and thus classifies this medium to be inappropriate. Walther et al. argue that computer-mediated communication can be as capable as a face-to-face interaction since the nonverbal cues that are lost when communicating e.g. via e-mail are replaced by a greater focus, interaction partners set on the cues that are left (such as the textual content of the message, the use of emoticons or the timestamp of a message). Thus, it is possible that a relationship between interaction partners (which is seen as a crucial element of successful joint fulfilment of a task) is developed which is comparable to a face-to-face setting – although it is argued that this development takes more time. This point of view is – similarly to the aforementioned one – known as the *cues-filtered-in* model. [35]

This paper outlines the idea of using methods of machine learning on a corpus of messages exchanged in electronic negotiations to further understand communicational aspects of this kind of discourse. It thus follows the approach presented above, that social cues are still conserved in the interaction data of an electronic negotiation. The idea is to be able to identify influencing factors of successful und unsuccessful negotiation, and to use them to create a prediction scheme which can be applied to ongoing negotiations. First, a brief overview over related and similar fields in this context is given, also presenting some results with similar goals, while afterwards the general problem that this paper addresses is described. The applicability of machine learning on electronic negotiations is reviewed and the first steps of analysis, namely data preparation and feature selection are presented. The data used for the approach consists of several hundred bilateral electronic negotiations that were conducted during different experiments in recent years at the University of Hohenheim. According to the specific characteristics of this data and the task given, a scheme will be developed to evaluate the applicability of different feature selection measurements. Finally, leading questions and ideas will be formulated and an outline of the further research steps is given.

# 2 A review on existing methods and findings in analysing negotiation communication

## 2.1 Linguistic Approaches

Communication in electronic negotiation has already been analysed from various different points of view. Often, communication is (obviously) studied with traditional, linguistic approaches. Sokolova et al. ([30] and subsequent publications) have contributed considerably to this idea over the past ten years. Their approach (as described for example in [28]) isto construct a corpus from experimental data of electronic negotiations (for the construction of linguistic corpora, see for example [8]). The corpus is analysed afterwards by methods such as n-gram analysis techniques [28], and, in later publications, machine learning techniques are applied to extract strategies from the negotiation texts [29]. Note that the current paper and the proposed future research in chapter 5 are strongly related to their work, with the main difference being that Sokolova et al. apply a domain-specific scheme to represent the negotiation data (see [26] and [27]) while this paper explores the applicability of general methods of feature selection.

## 2.2 Artificial Intelligence Approaches

The idea to use more complex approaches to analyse negotiation communication is not a new one. Sidelines of the artificial intelligence field have already been applied to predict single negotiation steps or even outcomes of a negotiation. An example for this is provided in [31], applying Markov chain analysis to negotiation fragments. First, a coding process is applied to single negotiation utterances to determine whether they are integrative or distributive. Afterwards, first-order and second-order Markov models are used to analyse reciprocity in communicative behaviour, i.e. to what extent integrative behaviour is reciprocated by integrative behaviour and vice versa.

## 2.3 Findings in the context

Influencing factors for successful negotiations on the level of communication have been the subject of previous studies. Some of the findings in this context, which may be particularly interesting for the presented approach, are summarised below.

*The influence of emotions on negotiations:*

One of the main influencing factors that are expressed in the negotiation communication itself are the emotions communicated. Especially in face-to-face negotiation, much scientific work has been conducted in this context, trying to find out how exactly which kind of emotions influences which of the outcome variables of a negotiation:

On effectiveness for example Brett and Olekalns [3] found that negotiations where negative emotions were communicated were less likely to succeed. Also, more generally, this occurred when a partner was threatened with loss of face. Friedman et al. [11] argued that expressions of anger trigger the same reaction by the counterpart (“reciprocity of emotions”) and thus make settlements less likely.

Similarly, especially negative emotions are also influencing efficiency of a negotiation and, more generally speaking, the collaborative execution of tasks. Several studies exist that analyse this influence (e.g. [18], [2]) by using designs where negotiators were manipulated to express specific emotions – positive or negative – or to perceive their partner as competitive and aggressive. Li and Roloff [18] found that whilst negotiators in a positive setting tend to get higher joint outcomes, negotiators applying negative emotions receive a better outcome on the individual level. This was also reflected in a higher level of satisfaction with the outcome in negative dyads. However, the positive or negative effect of emotions on negotiations is a complex topic, which is highly context-dependant. It is also argued that negotiators showing positive emotions reach higher joint and individual gains, since showing happiness shows motivation and enables creativity to find solutions fitting best on individual and joint level (e.g. [34]).

*Communication quality and negotiation outcomes:*

Weigand et al. [36] employ a view of negotiation particularly regarding the communicative nature and thus the importance of communication quality (especially [24]) during the negotiation process. It is seen as crucial for a negotiation to be successful to show “good” communication quality, which can be decomposed into several parts: The development of a mutual understanding, structuring of the negotiation, coherence (i.e. taking up each other’s arguments), transparency and trust-building between negotiators. In this context, Duckek [7] applied methods of content analysis (detailed explanation e.g. in [32]) to negotiation experiment data and compared the results with those of an ex-post questionnaire of the experiment. One of the findings was that the aforementioned mutual understanding between negotiators is an influencing factor on the success or failure of a negotiation. ([7], p. 171).

*Other influencing communication factors:*

Throughout the negotiation literature and its related fields (i.e. social psychology, linguistics etc.), there are other findings which are grouped together in an incomprehensive list in this section:

According to Swaab et al. [33], negotiation outcomes can be directly influenced by a negotiator simply by mimicking the language of the counterpart and acting in a similar way. The experimental findings show that, when performed at an early stage of the negotiation, mimicking the partner can increase individual outcome of a negotiator. However, when excessively performed in the later stages of the negotiation, it has the opposite effect.

Concerning efficiency, Adair and Brett [1] argue that negotiations having had an exchange of priority information and affective persuasion at an early stage, negotiation outcomes tend to be better in terms of joint outcomes and the exploitation of integrative potentials.

Taken together, these findings and the approaches mentioned in 2.1. and 2.2. indicate that it could be possible to detect evidence for the further development of a negotiation at an early stage using methods of machine learning (specifically text categorisation) to 1) find more specific patterns of success or failure of a negotiation and 2) apply these patterns to train a machine learning classifier, who can be able to predict the direction into which an ongoing negotiation may develop. This problem itself will be further defined in the following chapter.

# 3 Electronic negotiations as a Text Categorisation problem

## 3.1 A brief overview on Text Categorisation

During the past twenty years, a subfield of Data Mining has gained increasing attention: Text Mining. Especially since the striking success of the Internet during the mid-90s – and even more, the emergence of the Web 2.0 – huge amounts of unstructured or semi-structured content are generated every day. To find *interesting regularities* in this data (and textual data in general) is considered to be the core task Text Mining. From this definition it becomes clear that it is necessary to define what exactly “interesting” means, which is highly dependent on the task a researcher wants to perform.

Since it gained popularity in the 1990s, Text Mining has developed a variety of subfields, most of which are highly interconnected. From a Text Mining perspective, Text Categorisation (sometimes referred to as Text Classification or Document Classification) is among those subfields. Its main task is to assign categories to documents, depending on the textual content of these documents. These categories are usually specified in advance, so in most cases, text categorisation can be referred to as a *supervised* approach. To fulfil this categorisation task, it heavily draws on methods from related fields, such as *information retrieval, computational linguistics* or *machine learning* [8].

## 3.2 Electronic negotiations as a text categorisation task

According to Manning et al. [20], a text classification problem typically involves several elements: A document space $\mathbb{X}$ consisting of all available documents (i.e. negotiation messages) and a set of classes $\mathbb{C}$ consisting of the possible classes, the messages can be mapped to. In the case of negotiation messages this is defined simply as: $\mathbb{C} = \{\text{accept}, \text{reject}\}$ since on the most abstract level, we only have to predict the final negotiation outcome from the message. In terms of text categorisation, it can be considered as a binary classification task yielding a positive result if a message is classified as an indicator of a successful negotiation and a negative result for unsuccessful negotiations.

In our setting, we use two main simplifications to make the task accessible for a preliminary investigation: First, we introduce the assumption that the messages of a single negotiation are not related to each other. This enables us to increase our document space significantly, which is – as already stated – defined at the negotiation message level, not at the negotiation as a whole. Furthermore, we simplify the problem by assuming that a negotiation can either be successful or not, but not “partially” successful, so the categorisation problem is reduced to a *hard categorisation* task, in which each document is assigned to a single class, instead of returning a list of probabilities of document membership for the classes [25].

The method which decides to which class a document or a document subset belongs is called the *classification function* $\gamma$, or simply the *classifier* – typically, the goal of a machine learning algorithm is to determine such a classifier, which is defined as $\gamma : \mathbb{X} \to \mathbb{C}$. It is now possible to apply different learning methods, e.g. Naïve Bayes (a detailed description can be obtained in [17]), which are used on a subset of the documents, i.e. the training data, to estimate the classification function. Subsequently, the trained classifier is applied to test data (where the outcome is known) to obtain information about its performance, e.g. precision (i.e. percentage of negotiations classified as successful that are really successful) and recall (i.e. percentage of successful negotiations that are classified as successful) of the classifier (see [19]). It is important to keep the characteristics of the categorisation task in mind when deciding on quality metrics for classifiers, especially regarding precision and recall [9]. In our case, it is especially undesirable to classify negotiation messages belonging to failed negotiations as successful (see chapter 5). Therefore, in this situation precision is preferred over recall as a quality measurement.

# 4 Feature Selection as a preparative step for text mining

One of the biggest challenges in classifying text is the large dimensionality of the data. Typically (e.g. in a bag-of-words model), textual data for classification is represented as a vector, with each dimension representing the frequency of a term in the document. Due to the large vocabularies in typical corpora, this leads to a dimensionality that proposes a challenge to most common machine learning classifiers.[14] Therefore, machine learning research has developed a variety of strategies to overcome this 'curse of dimensionality', which are usually subsumed under the term feature selection. Its aim is to select the most characteristic features of the different classes of documents, and thus increasing not only efficiency of machine learning predictors but also precision and recall [25].

## 4.1 Data transformation as a pre-processing step for feature selection

In order to apply feature selection to data sets of natural communication, the communication data has to be prepared intensively first. Natural language (in our case in written form) is characteristically very noisy data, due to spelling errors, interjections etc., so this has to be taken into account as well. A simple, but quite effective method to remove misspellings is to prune words occurring infrequently. This threshold is usually not set higher than two, to avoid negative effects on precision of the classification. [10]

Finally, to prepare the data for the text categorisation steps, linguistic pre-processing techniques can be applied to reduce the dimensionality of the data. Typically, these steps involve the removal of stop words, stemming and lemmatisation. [8] This kind of pre-processing originates from Information Retrieval, where it is used e.g. to simplify search queries. However, the results of these techniques in text categorisation are mixed, since this reduction of features comes with the price of a loss of information on the documents and therefore can affect the precision of a classifier, especially in situations where n-grams of common words provide important semantic information. (see also [14], p. 1165 for similar argumentation).

## 4.2 An overview on different types of feature selection methods

Feature selection techniques typically are distinguished into three classes, according to the way they are applied in a classification task:

*Filtering methods:*

A filtering point of view is the most distinguished one, because feature selection is seen as a task not related to the classification technique applied. A filtering method applies a scoring technique to all units occurring in the document collection (which can be words, sentences, n-grams, etc.) and filters out those units which achieve the lowest score in being characteristic for a class (or, respectively selects the k features with the highest scores). Common scoring methods are for example Document Frequency, Mutual Information,

Information Gain, Term Strength and the $\chi^2$-Statistic.[37] The discussion of a selection of these methods and their usefulness for the task of classifying electronic negotiation data is the main focus of chapter 4.4.

*Wrapper methods:*

Wrapper models perform feature selection by defining all possible subset of features that can be used as a search space. Then, typical Artificial Intelligence search algorithms (such as hill-climbing, simulated annealing, genetic algorithms, etc.) are applied to find the most useful subset of features. The particular interesting clue of a wrapper method is that the subsets are evaluated by their scores on the same classifier that is used afterwards. Hence, the quality of the wrapper method is determined by three influencing factors: The search algorithm, the classifier used for evaluation, and the way the classifier's performance is measured [14]. In tasks where non-textual data is analysed, wrapper methods are found to perform quite well. [9] Concerning text categorisation, applying a wrapper model poses a challenge in computational complexity, since the search problem is known to be NP-Hard [14], and it is thus extremely expensive to apply these methods, since they are not designed to be used on too many features – which is also the reason why they will not be taken into account any further in this paper.

*Embedded methods:*

Embedded methods are not actually feature selection methods themselves. Rather, they refer to a specific type of classifier which performs the feature selection in an implicit way during the training phase. An example which is known for its good performance on text categorisation tasks is the Support Vector Machine (SVM) [4]. Nevertheless, depending on the characteristics of the data, they can be combined with preparative filtering of features to further increase their performance [13]. But since they are not inherently techniques to select features, the evaluation will focus on the filtering methods. Note that since embedded methods have been proven to work efficiently on text categorisation problems, they will be taken into account for the classification task itself.

## 4.3 Criteria imposed by the task itself and the data present

This part is to discuss different methods of feature selection, especially taking into account their applicability on electronic negotiations. Factors included in this evaluation are:

- Noise sensitivity: The negotiations, as already mentioned in chapter 4.1 consist of very noisy data. Even after spell-checking and standard cleaning methods, this noise can bias the result of the feature selection. Therefore, an appropriate method should be as insensitive to noise as possible.
- Effect on quality metrics: Since negotiating a multiattribute agenda is a complex and multi-faceted task, we expect the decision whether a negotiation is successful or not to depend on a comparably high number of different features. Therefore, a preferred method has to have a positive impact on quality metrics, even if a large feature subset is selected from our data.

- Class Skew: Often in binary text categorisation, problems occur if the classes to be evaluated are imbalanced. A classifier can be biased by this imbalance, and simply classify every document into the class with the higher amount of documents, leading to high classification accuracy but of course not to desired results. Our data consists of 4162 messages from successful negotiations and 1060 messages from unsuccessful negotiations, resulting in a skew of approx. 1:4, which is acceptable, but nevertheless should be taken into account as a criterion.
- Computational complexity: Since typically, text categorisation problems involve high-dimensional data, a feature selection must be capable to produce an output of selected features within an appropriate timeframe. Therefore, methods of high computational complexity will be ruled out by the scheme

### 4.4 Discussion of selected methods

| | Noise sensitivity | Effect on quality metrics | Sensitivity to class skew | Computational complexity |
|---|---|---|---|---|
| Document Frequency | Good, if noise terms happen to be rare terms [37] | Surprisingly accurate, contradicting the assumption that rare terms carry significant information in TC (until up to 90% term removal) [37]<br>But performing bad up to 1000 features selected [9] | Pays attention only on the positive features, not on negative features. Therefore, skew bias to be expected. | Linear in document space [37] |
| Information Gain | - | Peaking at ~2000 features (F-Measure) [37] | Bias towards positive features [39], but: best performance under low-skew conditions [9] | Linear in Vocabulary space (for binary classification tasks) [37] |
| $X^2$ Statistic | "Known to not be reliable for low frequency terms" [37] | Highest effect between 100 and 1000 features [20] (multinomial representation)<br>Peak at ~2000 features (F-Measure) [37]<br>Generally outperforming other metrics [37], especially in combination models [22] | Strong bias towards positive features[39] | Quadratic [37] |
| Odds Ratio | - | Comparable performance to $X^2$ and IG, though slightly lower [9] outperformed by $X^2$ and IG [39] | One-sided metric, performance lower due to disregard of negative features [39] | Quadratic |

**Table 1: Feature Selection methods aligned with criteria**

Out of the filtering methods commonly known and applied to text categorisation settings, four were investigated on their usefulness for the negotiation data – the information shown in table 1 are taken from different comparative studies on feature selection ([9],[37]).

Interestingly, most studies only mention data noise as an influencing effect as a side note or not at all. The general opinion is that most of the noise can be removed, when rare terms are removed as mentioned in chapter 4.1. This is to some extent contradictory to the general assumption that rare terms carry relatively much information, but has been shown to work surprisingly efficient in text categorisation tasks [37]. However, information obtained from the studies that exist states that particularly document frequency and the $X^2$-statistic can be negatively influenced by terms that occur rarely in the document – an effect that of course can be smoothened by applying the reduction by term frequency mentioned above.

Concerning the general performance of the techniques (or, respectively the performance of a classifier when the feature selection method is applied), it is reported that all of the methods mentioned show a decrease when more than 2000 features are selected. (Macro-averaged F-Measure) [9]. Especially IG and $X^2$ have been shown to be good performers when the precision of the classifier is the crucial measure. It is also the common opinion of the main studies reviewed that $X^2$ tends to be the strongest performer of the given methods ([9],[37]), with classifiers still performing highly accurate in settings where up to 90% of the features are removed. [22] Interestingly, Yang and Pedersen [37] also report a correlation between Document Frequency, Information Gain and $X^2$, which to an extent explains their similar behaviour considering performance.

For the skew analysis, basically two things can be taken into account: Firstly the effects on performance [9], and secondly the inner workings of the method used, especially if the methods pay attention not only to positive features (indicating membership to a category) but also to negative features (indicating explicitly that a term is not relevant for a class) [39]. The findings of Forman [9] show that in a low-skew situation (which is present here), Information Gain tends to outperform the other metrics. These results are in line with the argumentation of Zheng et al. [39], pointing out $X^2$ and IG as two-sided metrics which also pay attention to negative features – although being biased towards positive features. Since this bias is reported to be stronger for IG than for $X^2$, these findings appear consistent.

Lastly, the criterion of computational cost shows, that all of the selected methods are of manageable complexity, with DF being linear in the document space as the presumably cheapest method.

In conclusion, especially $X^2$ and IG seem to be the most promising feature scoring metrics from an argumentative point of view, because of their suspected low bias when noise is filtered out before applying the scores, because they tend to outperform the other presented scoring methods, especially in low-skewed situations, because they regard positive as well as negative features, and because the computational complexity of applying them is manageable.

Note that a comprehensive evaluation of these techniques is rather difficult because of the large amount of parameters that can be changed, regarding the data set used for the comparative studies, preparation steps applied (spelling correction, stemming, lemmatization, stop word removal, removal of infrequent words,…) data representation (binary, word count, frequencies, normalized frequencies, uni-grams vs. n-grams,…), amount of features selected, quality metrics for evaluation and the classifier used to determine the effect of the selection method.

# 5 Outlook: Future research

The paper discusses the possibility to apply text mining and, specifically, text categorisation on negotiation message data and presents these different fields. Also, first steps of the approach were conducted, by reviewing different feature selection methods, as presented in chapter 4. Clearly, future work on this topic is needed since it is a very promising approach to understand comprising elements of negotiation communication further and, especially, to distinguish “good” communication form “bad” communication. This is not only interesting on a semantic level, it may also be used to create a method for an early detection of potentially unsuccessful negotiations.

Therefore, in future steps, a classifier has to be trained on the features created and it has to be checked, how different classifiers behave when confronted with the negotiation data. If negotiation classification would work with a satisfying quality, the potential of an application of a classifier at early stages of a negotiation process can be tested, with the final goal being to create a method that proactively supports negotiation communication – so that it would be possible for a negotiation support system to intervene at an early stage, if the negotiation is likely to fail, thus leading to more successful negotiations resulting in higher agreement rates.

Also, in the case that classifiers will not provide satisfying results, there is still potential in the idea proposed: One could drop the assumption made in chapter 3.2, defining the problem as a hard categorisation task. According to Sebastiani [25], in such a task a human expert should make the final decision on the class to which a document belongs. In an ongoing negotiation, this step could be done by a mediator, who interprets the output of the system. Also, it would be possible to define a threshold for the resulting probabilities. If for example this threshold on the probability of failure is exceeded, the negotiation support system could ask the negotiators whether support (e.g. mediation) is required.

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